Are European natural gas markets connected? A time-varying spillovers analysis

Monika Papież[a], Michał Rubaszek[b], Karol Szafranek[b], Sławomir Śmiech[a]

[a] Cracow University of Economics, Department of Statistics, Rakowicka 27 St., 31-510 Cracow, Poland

[b] SGH Warsaw School of Economics, al. Niepodległości 162, 02-554 Warsaw, Poland.

Abstract

This paper examines the European natural gas market connectedness. Four main markets from the North-Western and South European regions are investigated with the Diebold-Yilmaz connectedness approach derived from the time-varying parameters VAR model with stochastic volatility. We show that the European natural gas market becomes increasingly integrated. Our results invalidate previous findings which pointed to the leading role of the British NBP as a source of shocks to natural gas price and volatility. Instead, we demonstrate that the two leading markets in Europe are the Dutch TTF and the German NCG. In recent years, however, the observed dominance of the indicated markets weakens, while spillovers from the Italian PSV gain importance. This could indicate the growing role of the supply of LNG and the launch of the pipeline from the Caspian Sea to Italy via Southern Europe.

Introduction

Reducing greenhouse gas emissions to keep global warming below 1.5°C, a goal set within the Paris Agreement, is one of the greatest global challenges. In European countries, policies aimed at meeting this target are predominantly focused on increasing the share of renewable energy sources in the energy mix, reconsidering the use of nuclear energy and replacing coal and lignite power plants with natural gas ones. The reason for the latter is that natural gas power plants emit twice less CO_2 compared to coal ones. At the same time, they are also more dispatchable, which makes them a suitable complement to the volatile supply of energy from renewable sources, mostly wind. For the above reasons, the share of natural gas in electricity generation in the EU countries has increased considerably over the last two decades. In years 2000-2020, this share jumped from 13.6% to 20.2%, as electricity production in gas plants increased from 363 TWh to 732 TWh (IEA, 2020).

The important role of natural gas in the energy transition in Europe is reflected in policy decisions which have led to the creation of a competitive internal gas market. The two Gas Directives introduced in 1998 (98/30/EC) and 2003 (2003/55/EC) were aimed at developing infrastructure, gas installations, retail supply, transmission and distribution. The third Gas Directive of 2009 (2009/73/EC) tightened the requirements for unbundling network activities related to supply and production. The most recent Gas Directive of 2019 (EU, 2019/692) states that the pipelines connecting the EU countries to third countries should be subject to the EU regulation which addresses the development of the second NordStream gas pipeline connecting Russia with Germany.

These changes in regulations have led to the development of gas hubs in European countries and to a gradual, but profound, change in price formation mechanisms. According to the International Gas Union Survey (IGU, 2021), the share of oil-indexed contracts in total transactions declined from 72% in 2005 to 20% in 2020. During the same period, the share of gas-on-gas contracts increased from 15% to 80%. Moreover, European buyers systematically shift from long-term contracts towards short-term ones. Consequently, the liberalization process has increased market transparency although has not contributed to the improvement in the area of energy security. Since the EU countries do not have significant domestic gas resources, its demand must be satisfied through imports. According to Eurostat, the main gas suppliers to the EU countries in 2020 were Russia (43.9% share in gas supply), Norway (19.9%), Algeria (11.9%), the United Kingdom (5.5%) and the United States (5.0%). Regarding domestic production, in 2020 it represented 7.2% natural gas consumption. It can be added that the Netherlands, i.e., the major gas supplier within the EU, has been successively phasing out

its production from the Groningen field, with a drop in production reaching -28.3% between 2019 and 2020. It is also worth noting that most gas is supplied via pipelines, but LNG supplies have increased gradually in recent years. Finally, the ultimate country of origin of natural gas supplied to the European countries is heterogeneous – Russian supplies serve Central European countries, including Germany, Norwegian gas tends to be delivered to Northern European countries, whereas Southern European countries rely mainly on gas from Northern Africa, with the exception of Italy, which is also heavily dependent on Russian gas.

The result of the liberalization process is that currently gas hubs – which provide either physical or virtual trading of this commodity – are central to the organization and liquidity of the market. According to Heather (2021), two European hubs can be considered to be mature in terms of their liquidity and transparency: the Title Transfer Facility (TTF) in the Netherlands and the National Balancing Point (NBP) in the United Kingdom. The TTF dominates gas hubs in Europe in terms of traded volume. In 2020, it stood at 46.7 PWh, compared to 10.1 PWh for the NBP, 2.0 PWh in the German hub (Net Connect Germany, NCG) and 1.5 PWh in the Italian hub (Punto di Scambio Virtuale, PSV). In recent years, the volume of trade has changed considerably in all these hubs. Between 2018 and 2020, it decreased by 33% for the NBP, while it rose by 65.4%, 37.3% and 11.6% for the TTF, PSV and NCG, respectively.

This development of gas hubs in Europe as well as the heterogeneous sources of natural gas supplies in the European countries call for the following question: which hubs dominate others in terms of price formation and volatility transmission? To answer it, we employ the Diebold and Yilmaz (2009, 2012, 2014) framework[1] to study the market connectedness in four most liquid European hubs (TTF, NBP, NCG and PSV). In our approach, we scrutinize both the relationship between price changes and volatility. Moreover, given the gradually changing structure of the European natural gas market, we apply the time-varying parameter stochastic volatility version of the underlying vector autoregressive (VAR) model. Specifically, we integrate the DY connectedness approach with the time-varying parameters VAR model with stochastic volatility (hereafter TVP-VAR-SV) proposed by Primiceri (2005), which is a framework that allows all model parameters to evolve continuously in time according to an explicitly predetermined rule of motion. Despite heavy parametrization and non-trivial

[1] Naturally, other approaches towards quantifying connectedness in a multivariate setting have been put forward in the literature. These include multivariate GARCH models, which quantify dynamic correlations between variables (Engle, 2002); conditional value at risk measures, which quantify the tail dependency between the entire system and its chosen entity (Adrian and Brunnermeier, 2016); marginal expected shortfall tracking the sensitivity of rate of return for a single entity under extreme events (Acharya et al., 2016) or tail-event driven network risk (Härdle et al., 2016). While they are interesting approaches, we believe that the well-established connectedness methodology bests suits our research questions.

estimation, it allows us to quantify the dynamic connectedness between natural gas markets at each point in time, while simultaneously accounting for various types of underlying nonlinearities and controlling for heteroscedasticity heavily present in financial time series.

Our main findings can be summarised as follows. First, we show that in recent years the European natural gas market has become increasingly connected. Second, we distinguish the Dutch TTF and the German NCG as two leading markets that transmit shocks to the remaining hubs. However, in recent years, their dominance has markedly weakened, whereas the Italian PSV has gained importance. In this sense, our contribution to the literature is closely related to and constitutes an extension of the recent study conducted by Broadstock et al. (2020), who focus on three hubs located in Northern Europe (TTF, NBP and the Belgian Zeebrugge, ZEE). The extension comes from the three reasons. First, we cover the German and Italian hubs. Second, we provide results beyond 2019, which were characterized by record volatility. Finally, we use the TVP-VAR-SV model rather than the fixed-length rolling window VAR framework, which suffers from several limitations as discussed by Korobilis and Yilmaz (2018).

The remainder of the article is structured as follows. Section 2 reviews the literature. In Section 3 we outline the methodology. Section 4 describes the data, Section 5 contains the main results of our analysis, and the last Section concludes.

2. Literature Review

The literature on the linkages between European natural gas markets can be divided into two main strands related to the level of integration of the European markets and their connectedness.

The integration literature aims to establish the scale of convergence of natural gas prices in the European markets, a phenomenon expected as a result of the liberalization processes and the implementation of the relevant EU policies. Most studies focus on the North-West European markets and use daily spot or forward prices data. The main conclusion of these studies is that these markets are integrated. (Asche et al., 2013, 2001; Garaffa et al., 2019; Harmsen and Jepma, 2011; Neumann et al., 2006; Neumann and Cullmann, 2012) analyse the dynamics of gas markets in Belgium (Zeebrugge), the Netherlands (TTF), the United Kingdom (NBP), Germany (NCG or/and GPL - Gaspool) and France (PEG - Point d'Echange de Gaz). Asche et al. (2002), Growitsch et al. (2015), and Kuper and Mulder (2016) focus mainly on the German markets (NCG or/and GPL) and their links with the TTF hub. They find that the TTF is the benchmark hub and that these markets are reasonably well-integrated. Petrovich (2013), Heather (2015), Jotanovic and D'Ecclesia (2021) investigate many countries, including

Southern European ones. They also point to a strong integration of the European natural gas markets. Moreover, these studies illustrate the dominant role of the TTF, which is a benchmark hub. Finally, several studies find the convergence of industrial gas prices. Robinson (2007) and Renou-Maissant (2012) confirm that the law of one price holds in six Western European markets, whereas Bastianin et al.'s (2019) analyses of gas prices for industrial consumers in fourteen European countries reveal pairwise price convergence. Moreover, they demonstrate that the existence of trading hubs and the degree of interconnection are positively related to the existence of a convergence process.

Regarding the methodological frameworks employed in the integration literature, they range from standard cointegration analysis methods, such as the Johansen cointegration test (Asche et al., 2013, 2002, 2001; Petrovich, 2013), and its time-varying parameter version (Growitsch et al., 2015; Neumann and Cullmann, 2012; Renou-Maissant, 2012), to linear error correction models (Growitsch et al., 2015; Harmsen and Jepma, 2011; Jotanovic and D'Ecclesia, 2021), and their nonlinear alternative (Garaffa et al., 2019), to convergence tests (Bastianin et al., 2019; Neumann et al., 2006; Robinson, 2007).

The connectedness strand of the literature, which is the most relevant for our study, investigates mainly volatility spillovers across natural gas markets using the framework put forward by Diebold and Yilmaz (2009, 2012, 2014). Three studies in the literature on the connectedness of natural gas markets are particularly relevant. Scarcioffolo and Etienne (2019) consider daily prices from seven regional spot markets in the US and Canada in the period from 1994 to 2016. They find that over longer horizons, these markets are strongly connected, and shocks quickly propagate across regions. Interestingly, they also confirm that the connectedness of the markets has decreased in recent years due to a lack of pipeline capacity. Furthermore, they show that Henry Hub and Oneok are the two most active markets, both transmitting and receiving a significant amount of information. In their global market analysis, Nakajima and Toyoshima (2019) quantify the connectedness and frequency dynamics in North America, Europe and Asia–Pacific using daily data at four hubs, that is, Henry Hub, NBP, TTF, and JKM (Japan/Korea Marker) from 2009 to 2019. Using both the DY method and Baruník and Krehlík's (2018) methodology, they demonstrate that the global natural gas market is not integrated, which is consistent with the decoupling trend (Zhang and Ji, 2018). They only find strong links between the NBP and TTF, i.e., the two European hubs. Furthermore, their results reveal that in the global natural gas market, volatility spillovers are more pronounced than returns spillovers. Finally, Broadstock et al. (2020) study spillovers between three European natural gas markets (NBP, TTF, and ZEE) in the period from 2005 to 2018, based on price

returns and conditional price volatility obtained using standard GARCH techniques. They find that the integration of the European natural gas market has increased throughout the sample but is still not complete. Moreover, they prove that the TTF hub has a greater impact on price volatility in earlier periods and gains dominance over time in terms of both returns and price volatility. In contrast, the British NBP is the dominant hub in terms of its influence on returns in earlier periods. The NBP exerts a strong impact on other markets, and this effect intensifies over time.

Our study is most closely related to the last work. However, we complement this analysis from both a methodological and a cognitive perspective. First, rather than using the fixed-length rolling window VAR approach, we employ a novel methodology that integrates the well-established connectedness framework with the time-varying parameters VAR model with stochastic volatility. It enables us to alleviate several limitations of the former approach, which we discuss below. Second, we investigate the European natural gas market connectedness across hubs from various geographic locations and the level of liquidity, whereas the previous work examined the integration of hubs in close proximity. Third, we extend the analysis to account for the period of unprecedented market volatility associated with the outbreak of the COVID-19 pandemic and extremely low European natural gas inventories. Therefore, we learn how price formation and volatility are affected by adverse market conditions.

3. Methodology

To provide an assessment of the dynamic market connectedness, we start with estimating the time-varying parameters VAR model with stochastic volatility. Next, for each point in time, we calculate connectedness measures proposed by Diebold and Yilmaz (2009, 2012, 2014). In this section, we briefly describe the details of these two steps.

3.1. Time-varying parameters VAR with stochastic volatility

The dynamics of a n-variate dependent variable $y_t = [y_{1t}\ y_{2t} \dots y_{nt}]'$ is given by a VAR process of order P according to the following rule of motion:

$$y_t = B_{0,t} + \sum_{p=1}^{P} B_{p,t}\, y_{t-p} + u_t, t = 1, \dots, T \tag{1}$$

We allow all model parameters to vary over time. This concerns the vector of constant terms $B_{0,t}$, the coefficients of the autoregressive matrices $\{B_{p,t}\}_{p=1}^{P}$, and the variance-covariance matrix $\Omega_t = \left[\sigma_{ij,t}\right]_{n\times n}$ of model residuals u_t, as we assume that u_t follows a Gaussian process,

i.e., $u_t \sim \mathcal{N}(0, \Omega_t)$. The drift in the lagged coefficients is designed to capture possible nonlinearities and time variation in the lag structure of the model, whereas the variability in the error term describes the heteroscedastic structure of innovations in the system. By allowing for the variation in both parts of the model, we let the data determine the provenience of time variation, and we avoid spurious dynamics in random coefficients (Cogley and Sargent, 2005). We believe that overlooking time variation could lead to biased estimates of market connectedness as the European natural gas market becomes more and more integrated.

To estimate the parameters of model (1), we employ the method developed by Primiceri (2005) and refined by Del Negro and Primiceri (2015). Despite heavy parametrization and demanding estimation, this approach enables us to quantify various sources of nonlinearities present in the system and pin down the varying magnitude of shocks, as all model parameters evolve continuously in time (Lubik and Matthes, 2015; Ng and Wright, 2013). It can be added that this method has recently become increasingly popular in various investigations, in particular those related to the evolution and interplay of key macroeconomic variables (e.g. Bjørnland et al., 2019; Corsello and Nispi Landi, 2020; Lubik et al., 2016; Primiceri, 2005) or the developments in energy commodity markets (e.g. Anand and Paul, 2021; Baumeister and Peersman, 2013; Liu and Gong, 2020; Lyu et al., 2021; Wiggins and Etienne, 2017).

As argued by Primiceri (2005), matrix Ω_t can be decomposed as follows: $A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$, where A_t is a lower triangular matrix with ones on the diagonal and models the contemporaneous relationships among the endogenous variables in the model (i.e., the loadings), while Σ_t is the diagonal matrix of time-varying stochastic standard deviations. For the n-variate case, they are as follows:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & 1 & 0 \\ a_{n1} & \cdots & a_{nn-1} & 1 \end{bmatrix}, \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix} \tag{2}$$

To estimate the model efficiently, we use the above decomposition of Ω_t to re-write the model to the following form:

$$y_t = X_t' \beta_t + A_t^{-1} \Sigma_t \eta_t \tag{3}$$

where β_t is a vector collecting all parameters from $\{B_{p,t}\}_{p=0}^{P}$ and $X_t' = I_n \otimes [1, y_{t-1}, \dots, y_{t-P}]$, with $\otimes$ being the Kronecker product. Regarding the error term, in the above specification $\eta_t \sim \mathcal{N}(0, I_n)$ so that $A_t^{-1}\Sigma_t\eta_t = u_t$.

Following Primiceri (2005), the time-varying parameters from vector β_t and the free elements of matrix A_t, which are stacked row-wise into α_t, are governed by the standard random walk process, whereas the vector of standard deviations σ_t from the diagonal of matrix Σ_t follows the geometric random walk. Consequently, they are specified as follows:

$$\beta_t = \beta_{t-1} + \nu_t \tag{4}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{5}$$

$$\log \sigma_t = \log \sigma_{t-1} + \varepsilon_t \tag{6}$$

All innovations in the system are assumed to be mutually independent and normally distributed with the variance-covariance matrix:

$$Var\left(\begin{bmatrix} \eta_t \\ \nu_t \\ \zeta_t \\ \varepsilon_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{7}$$

where Q, S and W are positive-definite time-invariant matrices. For matrix S, a block-diagonal structure is imposed as in Primiceri (2005) to simplify inference and increase estimation efficiency.

The parameters of the model are estimated using Bayesian methods, specifically the Markov Chain Monte Carlo (MCMC) approach and the Gibbs sampler of Del Negro and Primiceri (2015). For the prior information, we follow standard choices in the literature (e.g. Anand and Paul, 2021; Bjørnland et al., 2019; Chatziantoniou et al., 2021; Czudaj, 2019; Lubik et al., 2016; Lyu et al., 2021) proposed by Primiceri (2005). In the first step, we set the prior for the initial value of model parameters, i.e., β_0, α_0 and $\log \sigma_0$, by using point estimates from the time-invariant VAR model estimated on pre-sample observations. Consequently, $\hat{\beta}_{OLS}$, $\hat{\alpha}_{OLS}$ and $\hat{\sigma}_{OLS}$, as well as the respective variance matrices $\hat{V}(\hat{\beta}_{OLS})$ and $\hat{V}(\hat{\alpha}_{OLS})$, serve as parameters of the prior distribution:

$$
\begin{aligned}
\beta_0 &\sim \mathcal{N}\left(\hat{\beta}_{OLS}, k_\beta \cdot \hat{V}(\hat{\beta}_{OLS})\right) \\
\alpha_0 &\sim \mathcal{N}\left(\hat{\alpha}_{OLS}, k_\alpha \cdot \hat{V}(\hat{\alpha}_{OLS})\right) \\
\log(\sigma_t) &\sim \mathcal{N}\left(\log \hat{\sigma}, k_\sigma \cdot I_n\right)
\end{aligned} \tag{8}
$$

Regarding the hyperparameters specifying the tightness of the prior, we set them to the standard values from the literature, i.e., $k_\beta = 4$, $k_\alpha = 4$, $k_\sigma = 1$.

Next, we impose the prior on matrices Q, S and W by assuming that:

$$
\begin{aligned}
Q &\sim \mathcal{IW}\left(k_Q^2 \cdot p_Q \cdot \hat{V}(\hat{\beta}_{OLS}), p_Q\right) \\
W &\sim \mathcal{IW}\left(k_W^2 \cdot p_W \cdot I_n, p_W\right) \\
S_j &\sim \mathcal{IW}\left(k_S^2 \cdot p_{S_j} \cdot \hat{V}(\hat{\alpha}_{OLS}), p_{S_j}\right) \text{ for } \mathrm{j} \in \{1, \dots, \mathrm{n}-1\}
\end{aligned} \tag{9}
$$

In this notation, $\mathcal{IW}$ denotes the inverse Wishart distribution, whereas $S_1, \dots, S_{n-1}$ denote blocks of matrix S of conformable size and corresponding to parameters belonging to separate equations of the TVP-VAR-SV model. Regarding the hyperparameters, we use the standard values of $k_Q = 0.01$, $k_W = 0.01$ and $k_S = 0.10$. Depending on the data we use, i.e., either daily logarithmic growth rates or weekly estimates of realized volatility, we set p_Q to either 250 or 52 to account for a year of pre-sample information and set $p_W = n + 1$ and $p_{S_j} = j + 1$, as is commonly done in the literature.

To estimate the model, we discard the first 5000 MCMC draws and retain the following 5000 draws. In reporting the results, we use the average estimates along with 68% credible sets. A detailed description of the TVP-VAR-SV model is comprehensively presented by Lubik and Matthes (2015).

3.2. Time-varying connectedness

The TVP-VAR-SV model can be integrated with the well-established connectedness methodology developed in a series of articles by Diebold and Yilmaz (2009, 2012, 2014). The initial proposition by Diebold and Yilmaz (2009) allows us to measure the overall (total) spillovers based on the forecast error variance decomposition from the structural constant parameter VAR model identified via the Cholesky factorization of the variance-covariance matrix. However, since such an approach is dependent on the order of variables in the model, refined frameworks (Diebold and Yilmaz, 2012, 2014) employ the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), henceforth KPPS. In this case, at the expense of shocks being correlated, the forecast error variance decomposition is invariant to the ordering of variables. Consequently, this framework enables the researcher, who is agnostic about the

direction of dependencies among variables, to quantify both total and bilateral spillovers. Therefore, it is a suitable econometric tool to capture market connectedness and establish which markets transmit (receive) spillovers to (from) other markets, both in aggregate and pairwise terms. Over the years, this methodology has attracted significant attention and has been extensively applied to study financial market interdependencies (e.g. Collet and Ielpo, 2018; Yarovaya et al., 2016), commodity markets linkages (e.g. Broadstock et al., 2020; Chevallier and Ielpo, 2013; Śmiech et al., 2019; Tiwari et al., 2020), volatility spillovers (e.g. Adekoya et al., 2021; Liu and Gong, 2020) and cross-country spillovers of macroeconomic variables (Antonakakis and Badinger, 2016; Elsayed et al., 2021; Hałka and Szafranek, 2016; Śmiech et al., 2020).

In this article, we integrate the DY framework with the TVP-VAR-SV model as we consider this approach to be extremely practical and elegant in obtaining time-varying market connectedness measures. It should be noted that since the work by Diebold and Yilmaz (2012) was published, in order to obtain dynamic measures of connectedness, the dominant approach in the literature has been based on the VAR model estimated in a rolling window (Broadstock et al., 2020; Chevallier and Ielpo, 2013; Collet and Ielpo, 2018; Diebold and Yilmaz, 2012; Elsayed et al., 2021; Hałka and Szafranek, 2016; Śmiech et al., 2019; Tiwari et al., 2020; Yarovaya et al., 2016). Unfortunately, as indicated by Korobilis and Yilmaz (2018), this approach has serious shortcomings. First, the results come at a cost of an arbitrary selection of the size of the rolling window –commonly far smaller than the sample size – which limits the degrees of freedom in the estimated constant coefficient VAR model. Hence, valuable information from the sample is sacrificed while the efficiency of estimation decreases, which can be problematic when dealing with data of relatively low frequency (e.g. monthly). Moreover, performing the rolling-window estimation leads to the lack of information on the connectedness in the beginning of the sample. Second, and more importantly, employing model re-estimation introduces spurious, excessive persistence into the connectedness measures, as they may elevate at an inadequately high level as long as data pertaining to the large shock remain within the window of analysis. The TVP-VAR-SV models allow an economist to overcome these shortcomings, mainly because they are commonly estimated via a Kalman filter, which is less sensitive to outliers than the traditional OLS approach used to estimate time-invariant VAR. Moreover, in our case, using the stochastic volatility component helps to account for volatility clustering present in the data, which is not done in the constant coefficient VAR model. These advantages of the TVP-VAR-SV approach have recently been recognized

by applied economists in a number of studies on market spillovers (Antonakakis et al., 2018; Korobilis and Yilmaz, 2018; Lin and Chen, 2021; Liu and Gong, 2020).

The starting point for integrating the DY framework with the TVP-VAR-SV model is to represent the model at time t in the form of the infinite moving average, i.e., $y_t = \sum_{s=0}^{\infty} \Lambda_{s,t} u_{t-s}$. Matrices $\Lambda_{s,t}$ of size $n \times n$ obey the recursion: $\Lambda_{s,t} = B_{1,t}\Lambda_{s-1,t} + B_{2,t}\Lambda_{s-2,t} + \cdots + B_{P,t}\Lambda_{s-P,t}$, with $\Lambda_{0,t}$ being the identity matrix and $\Lambda_{s,t} = 0$ for $s < 0$.This representation is key to understanding the dynamics of the system.

Following the DY framework, $\theta_{ij,t}^{g}(H)$ denotes the contribution of shocks to market i to the forecast error variance of market j at horizon H. The superscript g emphasizes the fact that the contribution is calculated with the KPPS generalized IRF method. The subscript t indicates that in our approach this statistic is a time-varying one. The formula is as follows:

$$\theta_{ij,t}^{g}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' \Lambda_{h,t} \Omega_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Lambda_{h,t} \Omega_t \Lambda_{h,t}' e_i)} \tag{10}$$

where Ω_t is the variance-covariance matrix for error vector u_t, $\sigma_{jj,t}$ is the jth element of the diagonal of matrix Ω_t and e_i is the selection vector with one as the ith element and zeros otherwise.

As shocks to each variable are not orthogonalized, the sum of the contributions to the variance of the forecast error may not necessarily be equal to 1. Therefore, the DY framework normalizes each entry of the variance decomposition matrix by the row sum, which we follow in our time-varying setting:

$$\tilde{\theta}_{ij,t}^{g}(H) = \frac{\theta_{ij,t}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij,t}^{g}(H)} \tag{11}$$

Hence, it holds that $\sum_{j=1}^{n} \tilde{\theta}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}^{g}(H) = n$.

Following the DY framework, we calculate the *total spillover index* using normalized forecast-error variance contributions from the KPPS variance decomposition. In our case, this measure is time-varying by construction and given by:

$$S_t^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \tilde{\theta}_{ij,t}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \tilde{\theta}_{ij,t}^g(H)}{n} \cdot 100 \tag{12}$$

By employing the generalized VAR framework, we can also learn about the direction of the spillovers. Consequently, we calculate:

Gross directional spillovers received by market i from all other markets j:

$$S_{i \leftarrow \blacksquare,t}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{n} \tilde{\theta}_{ij,t}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{n} \tilde{\theta}_{ij,t}^g(H)}{n} \cdot 100 \tag{13}$$

Gross directional spillovers transmitted by market i to all other markets j:

$$S_{\blacksquare \leftarrow i,t}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{n} \tilde{\theta}_{ji,t}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ji,t}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{n} \tilde{\theta}_{ji,t}^g(H)}{n} \cdot 100 \tag{14}$$

Net spillovers from market i to all other markets:

$$S_{i,t}^g(H) = S_{\blacksquare \leftarrow i,t}^g(H) - S_{i \leftarrow \blacksquare,t}^g(H) \tag{15}$$

Net pairwise spillover between markets i and j as the difference between the gross shocks transmitted from market i to market j and those transmitted from j to i.

$$S_{ij,t}^g(H) = \left(\frac{\tilde{\theta}_{ji,t}^g(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik,t}^g(H)} - \frac{\tilde{\theta}_{ij,t}^g(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk,t}^g(H)} \right) \cdot 100 = \left(\frac{\tilde{\theta}_{ji,t}^g(H) - \tilde{\theta}_{ij,t}^g(H)}{n} \right) \cdot 100 \tag{16}$$

Given that we work either with logarithmic rates of return or with weekly estimates of realized volatility, we set the horizon of our analysis to ten periods, i.e., $H = 10$.

4. Data on the EU gas markets

Given the important role of natural gas in the European energy mix, over the last 25 years the European Union has taken several actions to establish the legislative framework underlying the pan-European architecture of the market. Implementing the EU energy policy has aimed to guarantee the EU consumers a real competitive choice, ensure the security of gas supply and

create an internal energy market. Hubs, which are a vital element in the functioning of the European market, play a key role as platforms for physical or virtual transactions. We begin this section by describing the main characteristics of the European hubs and next describe the data used in our empirical investigation.

4.1. Characteristics of the European hubs

Selected information on the major European natural gas hubs is presented in Table 1. Looking at the chronology of their development, it can be noticed that the first three hubs were created in the period between 1996 and 2003: the NBP in the UK (1996), the Zeebrugge (ZEE) in Belgium (2000) and the TTF in the Netherlands (2003). The ZEE is the physical trading point, whereas the NBP and the TTF are virtual trading hubs. The British NBP was the most liquid hub in Europe up to mid-2010s, when this role was taken over by the Dutch TTF (Petrovich, 2013). Regarding the remaining hubs, the Italian PSV was created in 2003, and two years later, in 2005, the Austrian Central European Gas Hub (CEGH) and the three French hubs (PEG Nord, PEG Sud and TIGF) were launched. In 2015, PEG Sud and TIGF were merged into the Trading Region South (TRS), whereas in 2018 they were joined to PEG Nord to create the TRF (Trading Region France). The two German hubs, the Net Connect Germany (NCG in South Germany) and the Gaspool (GPL in North Germany), started operating in 2008 and 2009, respectively. In 2021, they were merged into a new nationwide German gas market called the Trading Hub Europe (THE). Other European hubs, such as the Spanish AOC (Almacenamiento Operativo Comercial), which replaced the PVB (Punto Virtual de Balance) in 2015, or the Czech VOB, are in the early stage of their development.

Table 1. Detailed information on major European natural gas hubs.

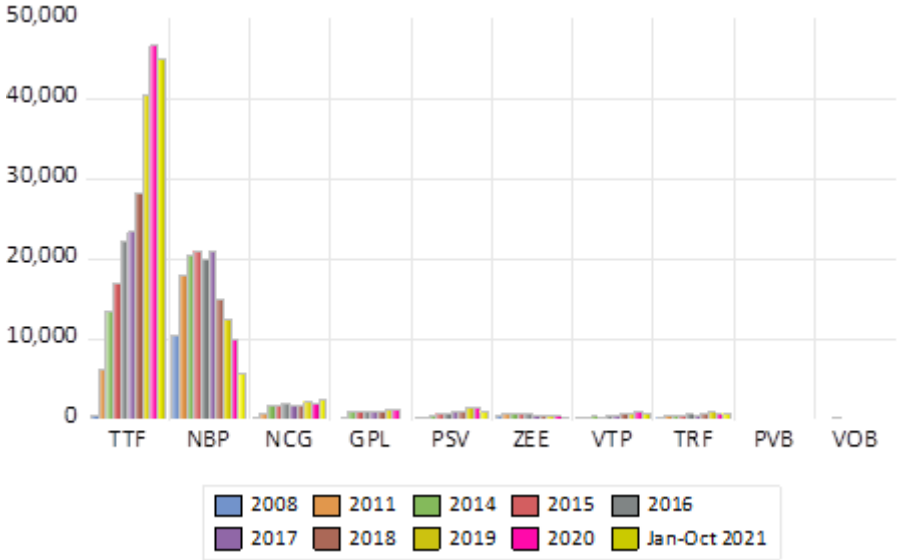
					Level of development in 2020		
Hub	**Country**	**Start year**	**Region**	**Volume [TWh]**	**Churn rate**	**Score**	**Type**
TTF	NL	2003	NWE	46 690	60.0	15	Mature
NBP	UK	1996	NWE	10 060	11.2	13	Mature
NCG	DE	2008	NWE	1 965	2.1	9	Active
GPL	DE	2009	NWE	1 350	1.6	9	Active
PSV	IT	2003	SE	1 455	1.9	10	Active
CEGH	AT	2005	CE	470	2.0	9	Active
ZEE	BE	2000	NWE	1 010	0.5	6	Poor
TRF/PEG	FR	2005	NWE	890	1.6	7	Poor
AOC	ES	2004	SWE	145	0.2	6	Poor
VOB	CZ	2011	CE	95	0.4	5	Poor

Sources: Heather, 2021, 2020, 2015; Heather and Petrovich, 2017.

Notes: All statistics refer to 2020. TTF - Title Transfer Facility, NBP - National Balancing Point, NCG - Net Connect Germany, GPL - Gaspool, PSV - Punto di Scambio Virtuale, CEGH - Central European Gas Hub, ZEE - Zeebrugge Trading Point, TRF - Trading Region France, AOC - Almacenamiento Operativo Comercial, VOB - Virtuální Obchodní Bod. NWE - North-West European region, CE - Central European region, SE - South European region, SWE - South-West European region.

We classify other characteristics of the European hubs by both their geographical location and their level of development. Table 1 reveals that most natural gas trade in Europe is conducted in the North-Western European region, i.e., the location place of NBP, TTF, NCG, GPL, ZEE and TRF/PEG. As far as the level of the development of hubs is concerned, Heather (2015) proposes five key elements (market participants, traded products, traded volumes, tradability index and churn rates) to determine which hubs are 'mature', 'active', 'poor', or 'inactive'. Table 1 shows that only two hubs (NBP and TTF) can be classified as mature, whereas four (NCG, GPL, PSV and CEGH) are active. This is also well illustrated in Figure 1, which depicts the trading volume of the analysed hubs and clearly indicates the dominant role of TTF and NBP. Between 2014 and 2021, the share of the trading volume of the two mature hubs was more than 80%, but the dominant hub has changed during this period (Figure 1). In 2014, the TTF traded volume was only 66% of the British NBP traded volume, while in 2020 the traded volume at TTF was more than four times larger than trade at the NBP. The change in the role of the dominant hub occurred in 2016, which can be linked to the outcome of the Brexit referendum. The dominant role of these two hubs is also confirmed by their churn rates (see Table 1), which describe the ratio between the total volume of trades and the physical volume of gas consumed in the area served by the hub.

Figure 1. Gas volumes traded, OTC day-ahead 2008–2021 (TWh).



Sources: Based on data from (Heather, 2021, 2020, 2015; Heather and Petrovich, 2017).

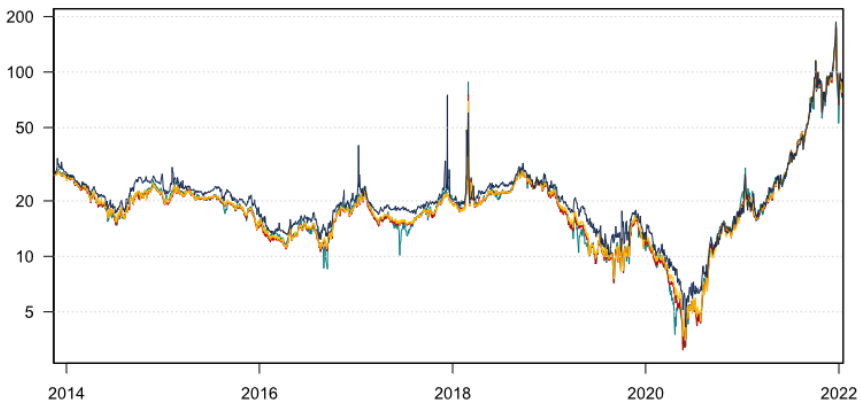
In our analysis, in addition to two mature hubs, we consider two active hubs, namely the German NCG and the Italian PVS. NCG ranks third in the hub rankings with the same score

of 10 points over the last few years. It was seven times smaller in terms of traded volumes than the TTF in 2014 and more than 23 times smaller in 2020. Given that Germany is continuing the process of creating only one hub for the whole country after the merger of hubs in 2011 and that Germany is Europe's largest gas demand market, has a comprehensive pipeline and storage infrastructure as well as good connections with all neighbouring countries, it is worth assessing the role of the German NCG hub in the European gas market. The Italian PSV, on the other hand, belongs to the Southern Europe region and is slowly climbing up the rankings. Heather (2021) comments that there is a strong political will in Italy for the PSV hub gas price to be the reference price for Mediterranean gas and for the PSV hub to become a route for LNG gas supplies to Northern Europe over time. These actions resulted in significant changes in the market structure, especially since 2014. Both churn rates, traded volumes and total scores are increasing: compared to 2014, the Italian PSV jumped from 6 to 10 in 2020.

4.2. Data

We analyse the connectedness among the European natural gas markets by focusing on four most important natural gas hubs: the NBP, TTF, NCG and PSV. We obtain daily series for day-ahead prices over the period from 15 November 2013 to 28 January 2022 from the Refinitiv Eikon database (former Thomson Reuters). Figure 2 presents the price series expressed in EUR/MWh. The plot shows that European natural gas prices are strongly integrated in the long run, which is in line with the literature surveyed in Section 2. However, in the short-run, there are periods of visible price differences in these markets.

Figure 2. Daily closing prices in four hubs: NBP, TTF, NCG and PSV in EUR/MWh.



Note: The green, red, orange and blue solid lines denote prices for NBP, TTF, NCG and PSV, respectively.
Source: Refinitiv Eikon.

The TVP-VAR-SV model with one lag is estimated separately for daily returns and for weekly volatilities. In the former case, we calculate log returns for each market i:

$$r_{i,t} = p_{i,t} - p_{i,t-1} \tag{17}$$

where $p_{i,t} = \ln P_{i,t}$, and $P_{i,t}$ is the closing price at day t. In the latter case, we follow Buncic and Gisler (2016), Liu and Gong (2020), Chatziantoniou et al. (2021) or Gong et al. (2021) and use a weekly estimate of realized volatility.[2] In this case, for each week s we calculate:

$$V_{i,s} = \ln\left(\sqrt{250 \sum_{t \in W_s} \frac{r_{i,t}^2}{T_s}}\right) \tag{18}$$

where W_s and T_s is the set and number of trading days in week s. Following Diebold and Yilmaz (2012), we calculate annualized volatility assuming 250 trading days within a year. Moreover, we reduce the impact of outliers and regularize the distribution by applying logarithms.

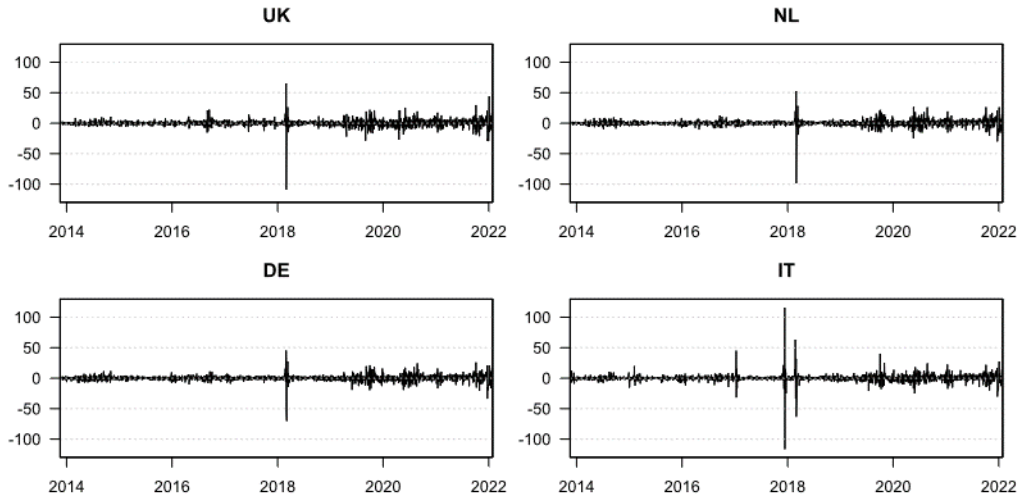
All series are presented in Figure 3, and their main characteristics are depicted in Table 2. It shows that there are 2057 observations for daily returns and 428 observations for weekly volatility series. Both the return series and volatility are skewed (negatively and positively, respectively) and extremely fat-tailed.

The Italian market turns out to be the most volatile one, whereas the German market is – in a figurative sense – the calm one. The largest daily returns for TTF, NBP and NCG occurred due to the late cold spell in early March 2018. The Italian PSV was affected by the cold spell to a lesser extent than Northwest Europe, and the market was in oversupply. However, the largest daily returns for PSV were on 12-13 December 2017 due to an explosion at the major European gas hub at Baumgarten in Austria, which is the key entry point for Russian gas into Austria and onward to Italy. On 12 December 2017, the day-ahead price at the Italian PSV hub almost doubled during one day, reaching record 80 Euro/MWh. The outage was quickly resolved, and prices soon receded. Additionally, it can be observed that from 2019 onwards, price volatility at all four hubs begins to increase.

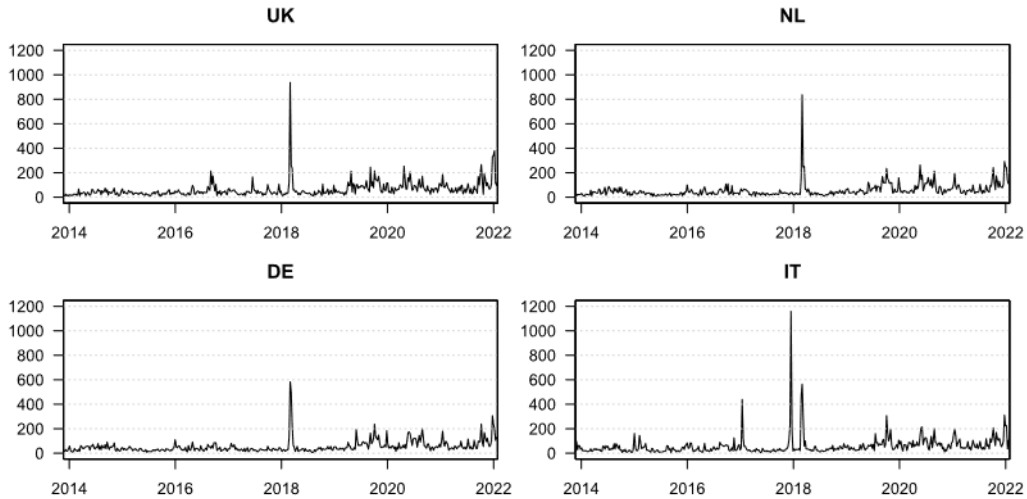
[2] The alternative would be to use range-based measures of volatility calculated using high, low, open, and close prices throughout the day (Alizadeh et al., 2002; Diebold and Yilmaz, 2012; Garman and Klass, 1980; Korobilis and Yilmaz, 2018; Parkinson, 1980).

Figure 3. Returns and volatility series for European natural gas prices.

A. Daily return series (%)



B. Weekly volatility series (%)



Notes: NBP hub for UK, TTF hub for NL, NCG hub for DE and PSV hub for IT. The time range refers to the period between 18 November 2013 and 28 January 2022.
Sorce: Refinitiv Eikon.

Table 2. Data characteristics.

Statistic	Daily return series				Weekly volatility series			
	NBP	TTF	NCG	PSV	NBP	TTF	NCG	PSV
Mean	14.0	14.8	14.7	14.9	61.4	55.2	53.8	58.2
Maximum	64.5	52.2	45.1	114.8	938.5	837.2	584.0	1160.2
Minimum	-108.4	-98.1	-69.9	-116.3	6.1	5.0	6.4	2.7
Std. dev.	89.2	79.9	74.8	98.8	65.4	57.9	52.5	79.1
Skewness	-2.6	-2.8	-1.6	-0.1	6.8	6.8	4.9	7.9
Kurtosis	79.7	79.5	40.8	127.1	77.9	79.2	37.4	94.6
Observations	2057	2057	2057	2057	428	428	428	428

Notes: The time range refers to the period between 18 November 2013 and 28 January 2022.

Next, Table 3 presents the correlation coefficients, which help to gauge the contemporaneous relationship between the markets. It shows that the links among the NBP,

TTF and NCG are strong for both the return and volatility series. In contrast, the correlation coefficients between these three hubs and the PSV are relatively low. This might be due to the fact that PSV is located in a different region than the remaining three markets.

Table 3. Correlation coefficients of the return series and the volatility series.

	Daily return series					Weekly volatility series			
	NBP	**TTF**	**NCG**	**PSV**		**NBP**	**TTF**	**NCG**	**PSV**
NBP	1.000				**NBP**	1.000			
TTF	0.845	1.000			**TTF**	0.899	1.000		
NCG	0.786	0.869	1.000		**NCG**	0.840	0.917	1.000	
PSV	0.494	0.514	0.524	1.000	**PSV**	0.544	0.542	0.549	1.000

Notes: All correlation coefficients are statistically significant (p-value < 0.01)

5. Empirical results

In this section, we describe the results of our investigation of the European natural gas markets connectedness. The TVP-VAR-SV model augmented for the DY measures, which are outlined in Section 3, is first applied to daily returns and next to weekly volatility series. In both cases, we start by presenting the detailed results for the first and last observations. Next, we discuss the evolution of the connectedness measures over the sample.

5.1. The results for daily returns

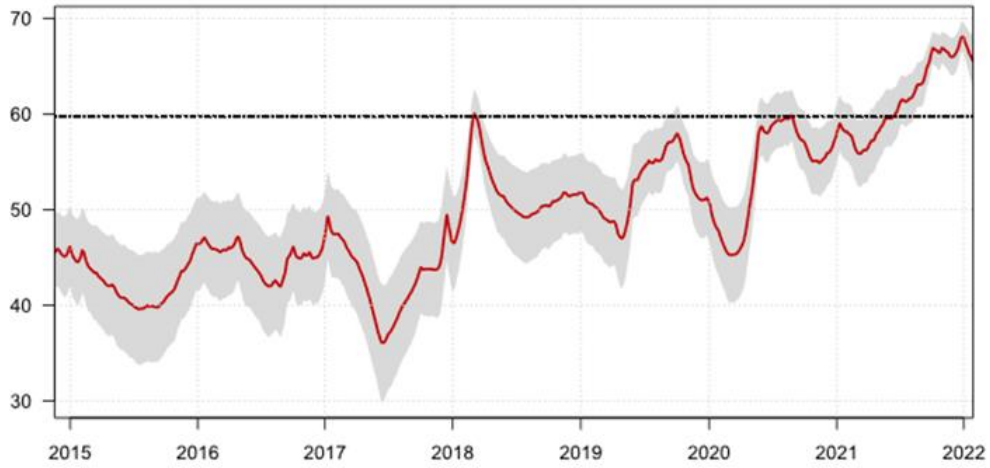
Table 4 presents the connectedness measures for the returns at the beginning (17 November 2014) and end (28 January 2022) of the main sample. The results indicate that throughout the sample, the total spillover index has increased from 45.5% to 65.6%. Second, the link of the PSV with the remaining hubs has been considerably strengthened. Specifically, in November 2014, the NWE region markets (TTF, NCG and NBP) were characterised by a high level of connectedness, although not with the Italian market. By comparison, in January 2022, the level of connectedness of all four markets is almost the same, which points to the successful process of integrating the Italian hub with the hubs of the NWE region. Third, the table shows that the TTF is the largest net transmitter of spillovers, followed by the German hub. In contrast, the NBP and PSV are net receivers. Finally, the table also demonstrates that over the investigated period, the role of the NBP has changed significantly. It has become the largest net receiver of spillovers. We attribute this to the fact that, following Brexit, the British market has lost importance at the expense of the TTF.

Table 4. Connectedness measures for the daily return series.

Initial sample – 17 November, 2014						Final sample – 28 January, 2022					
To / From	NBP	TTF	NCG	PSV	From others	To / From	NBP	TTF	NCG	PSV	From others
NBP	52.21	23.33	17.03	7.43	47.79	NBP	36.4	22.41	20.48	20.71	63.60
TTF	20.87	49.14	24.31	5.68	50.86	TTF	20.59	33.28	24.2	21.92	66.71
NCG	15.97	24.92	49.83	9.28	50.17	NCG	19.54	24.86	33.57	22.04	66.44
PSV	10.29	9.18	13.68	66.85	33.15	PSV	19.89	22.94	22.66	34.51	65.49
To others	47.13	57.43	55.02	22.39		To others	60.02	70.21	67.34	64.67	
NSI	-0.66	6.57	4.85	-10.76		NSI	-3.58	3.5	0.9	-0.82	
TSI					45.49	TSI					65.56

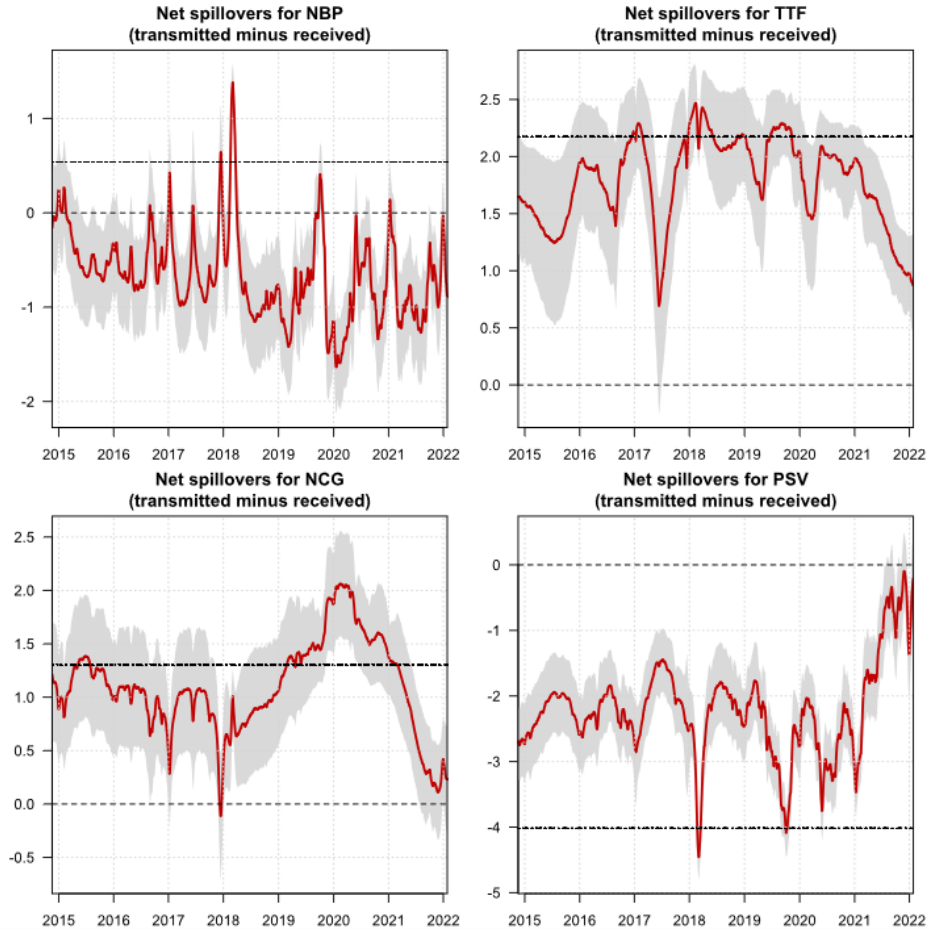
Notes: *ij*-th entry denotes the estimated contributions to the forecast error variance of market *i* from market *j*. The off-diagonal column sums ('To others') and row sums ('From others') are the 'to' and 'from' directional spillovers, respectively. The 'To others' minus 'From others' are the net spillover index (NSI). The TSI (Total spillover index) is the average of 'From others' (or 'To others').

Figure 4. Total volatility spillover index for the daily returns.



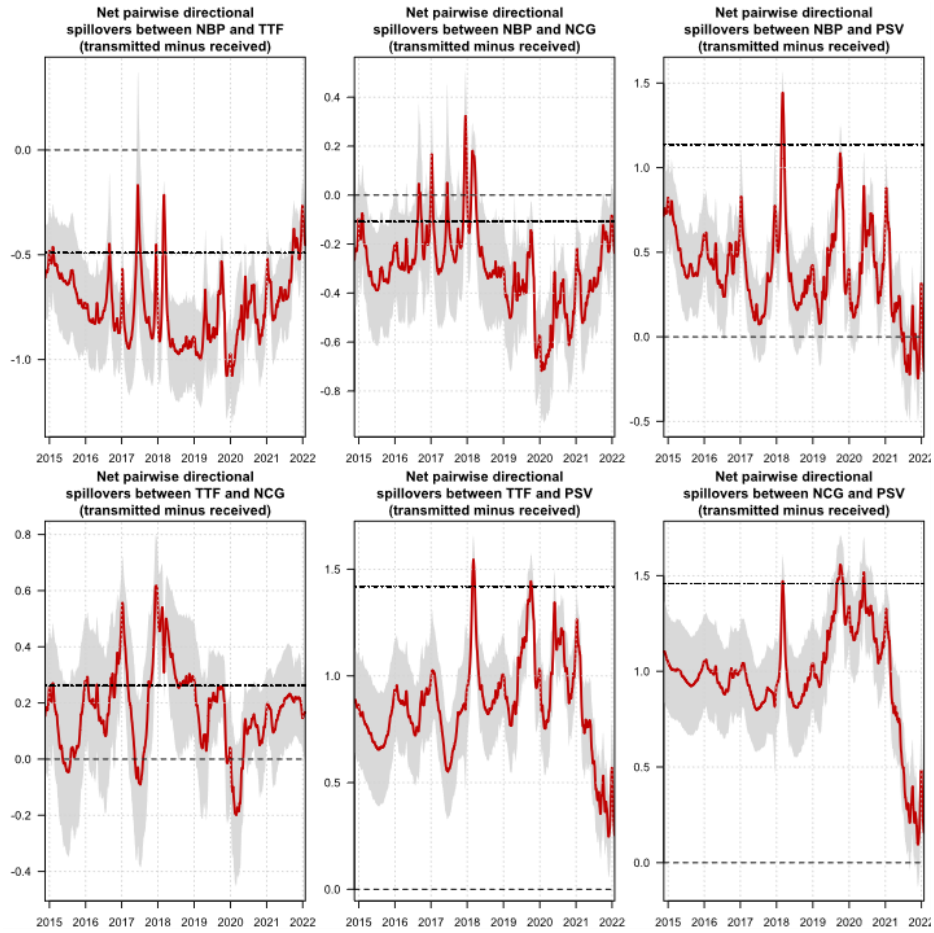
Let us now discuss the dynamics of the connectedness measures in the sample. Figure 4, which presents the evolution of the total volatility spillover index (TSI), shows that in years 2015-2017, the TSI fluctuated between around 40% and 50%. Next, starting from mid-2017, this index began to increase steadily from its trough of 36 to its peak of 67 in January 2022. The figure also illustrates that, apart from the long-term upward trend, there are significant short-term fluctuations in the index. For instance, in February 2018, during very cold winter (figuratively dubbed the 'Beast from the East'), the TSI jumped by more than 10 pp. By contrast, in March 2020, when the Covid-19 pandemic hit Western Europe, the TSI dramatically fell by about 15 pp.

Figure 5. Net spillover index for the return series.



Next, Figure 5 illustrates the changes in the net spillover index (NSI) calculated for the investigated European gas markets. Positive values indicate that a given market is a shock transmitter, whereas negative values mean that the market is a shock receiver. The figure indicates that the TTF and NCG have been net transmitters throughout the whole period of analyses, whereas the PSV and NBP have tended to be receiving markets. Importantly, the level of the NSI has evolved significantly over the sample. In the last year, the PSV shifted from being a net receiver (NSI at around 4 percent) into a neutral stance. This probably results from connecting Italy to a new gas supplier, Azerbaijan, via the TAP pipeline, which was launched in December 2020. This increased importance of the PSV is reflected in the declining role of TTF and NCG as transmitting markets. Finally, it can be seen that the value of NSI for the NBP has been relatively volatile.

Figure 6. Pairwise net spillover indices for the return series.



Finally, Figure 6 presents the evolution of the pairwise net spillover indices (PNSI) among the European natural gas markets, which allows us to gauge bilateral links between them. The figure shows that the TTF dominates over the remaining markets, transmitting shocks to the NBP and PSV, and to a lesser extent to the NCG. Next, when it comes to the interplay between the Northern market hubs and the Italian hub, it can be seen that until 2020 PSV received more than it transmitted from each of the other hubs, but during the last two years the net transmission has balanced out. This is especially visible in the pair against the NCG, in which the PNSI dropped from 1.5% to around zero. The last result that seems worth mentioning is that the NCG is a net transmitter against the NBP, which might be surprising given that the UK hub is more mature and liquid.

In general, the results for return spillovers, which are based on the TSI, NSI and PNSI connectedness measures, indicate that the gas market in Europe has moved toward a state of high integration in which there is no single market strongly dominating other markets.

5.2. The results for weekly volatility

Table 5 presents the connectedness measures for weekly volatility series at the beginning (28 November 2014) and the end (28 January 2022) of the main sample. It confirms the main results from the previous subsection, which point to a general increase in the total spillover index driven by strengthening the links between the SE and the NWE region hubs. In this case, the value of the TSI increased from 58% to 69% during the analysed period. Next, the table shows that the same hubs play similar roles as net transmitters and net receivers, i.e., the TTF and NCG transmit while the NBP and PSV receive volatility. However, the most noticeable difference between Tables 6 and 7 is that in January 2022, the NCG (and not the TTF) turned out to be the largest net transmitter of volatility. We interpret this outcome through the lens of the events that occurred in the market in winter 2021. Given the strong reliance of the NCG on supplies from Russia, heavy disruptions in the transfer of this commodity from this country to the EU and its unusually low inventories in major European economies, the German natural gas market was highly sensitive to any negative news related to the situation in Russia and hence transmitted a lot of volatility to other European gas hubs.

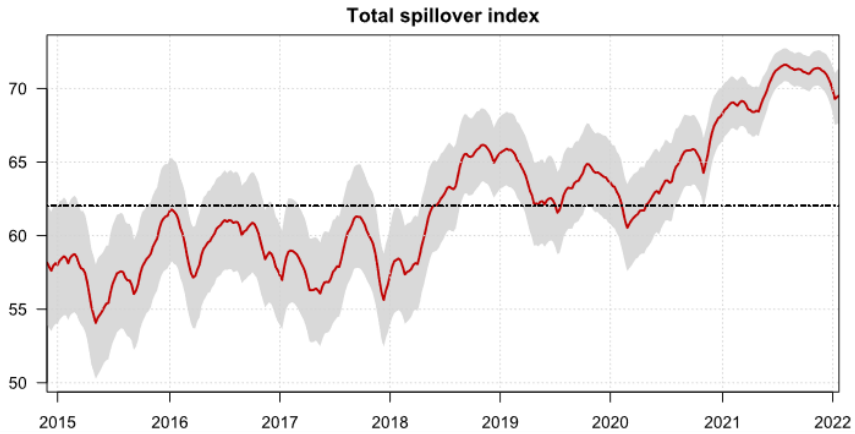
Table 5. Connectedness tables for the initial and final sample for the weekly volatility series.

Initial sample – 28 November 2014						Final sample – 28 January 2022					
To / From	NBP	TTF	NCG	PSV	From others	To / From	NBP	TTF	NCG	PSV	From others
NBP	39.09	25.23	22.76	12.91	60.91	NBP	30.00	24.11	24.36	21.53	70.00
TTF	20.48	40.16	25.35	14.01	59.84	TTF	21.25	30.03	27.31	21.40	69.97
NCG	19.28	28.34	36.76	15.63	63.24	NCG	20.91	26.83	29.89	22.37	70.11
PSV	13.62	18.83	16.26	51.30	48.70	PSV	20.97	22.64	24.38	32.01	67.99
To others	53.37	72.39	64.37	42.55		To others	63.13	73.58	76.05	65.30	
NSI	-7.53	12.55	1.13	-6.15		NSI	-6.87	3.61	5.94	-2.68	
TSI					58.17	TSI					69.52

Notes: *ij*-th entry denotes the estimated contributions to the forecast error variance of market *i* from market *j*; the off-diagonal column sums ('To others') and row sums ('From others') are the 'to' and 'from' directional spillovers, respectively. The 'To others' minus 'From others' are net spillover index (NSI). The TSI (Total spillover index) is the average of 'From others' (or 'To others').

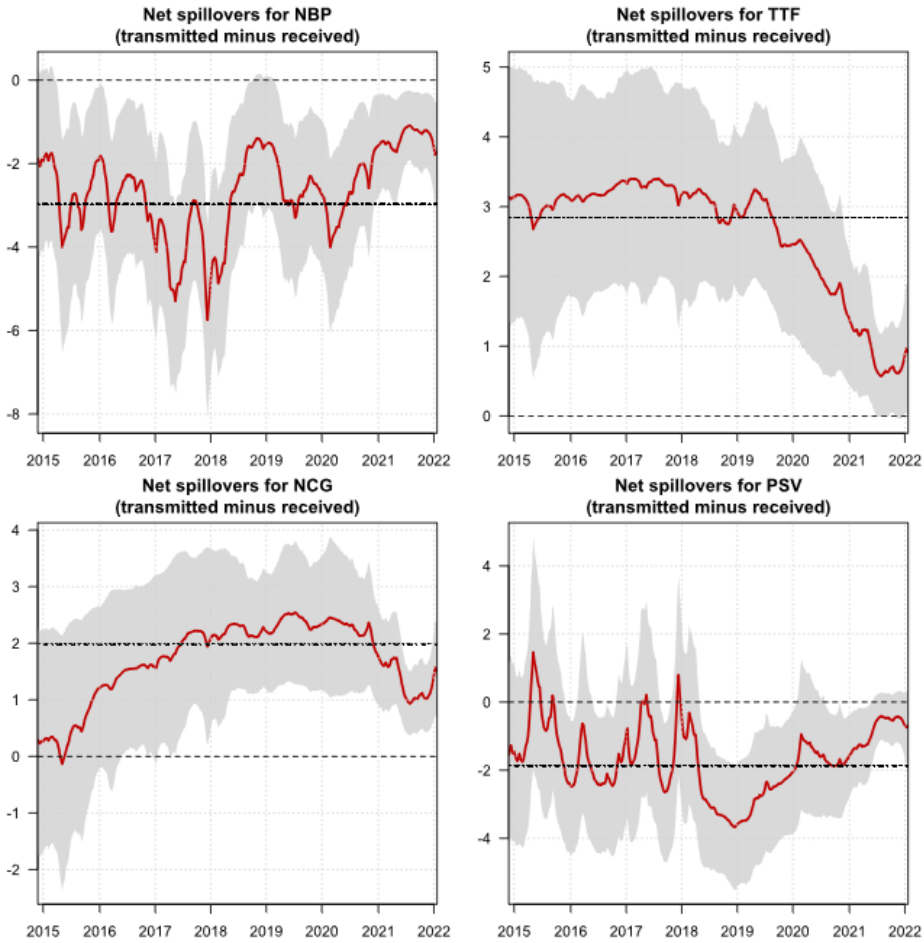
Figure 7 presents the evolution of the TSI for volatility over the investigated period. Apart from the gradual upward trend, three phases can be distinguished. In years 2015-2017, the TSI fluctuated between around 55% and 62%. Next, in the first half of 2018, it increased by about 10 pp and thereafter, in the period from mid-2018 to early 2020, stabilized at the levels between 60% and 65%. Finally, at the beginning of 2020, the TSI rose again to exceed 70% in the second half of 2021 and stayed at this very high level until the end of the sample.

Figure 7. Total volatility spillover index for the volatility series.



The net spillover indices for the volatility series are presented in Figure 8. Similarly to the NSI for returns, the TTF and NCG are net transmitters of volatility over almost the entire period, while the NBP and PSV are net receivers. It is noteworthy that for the last three years, the absolute difference between volatility transmitted and received has decreased in all hubs.

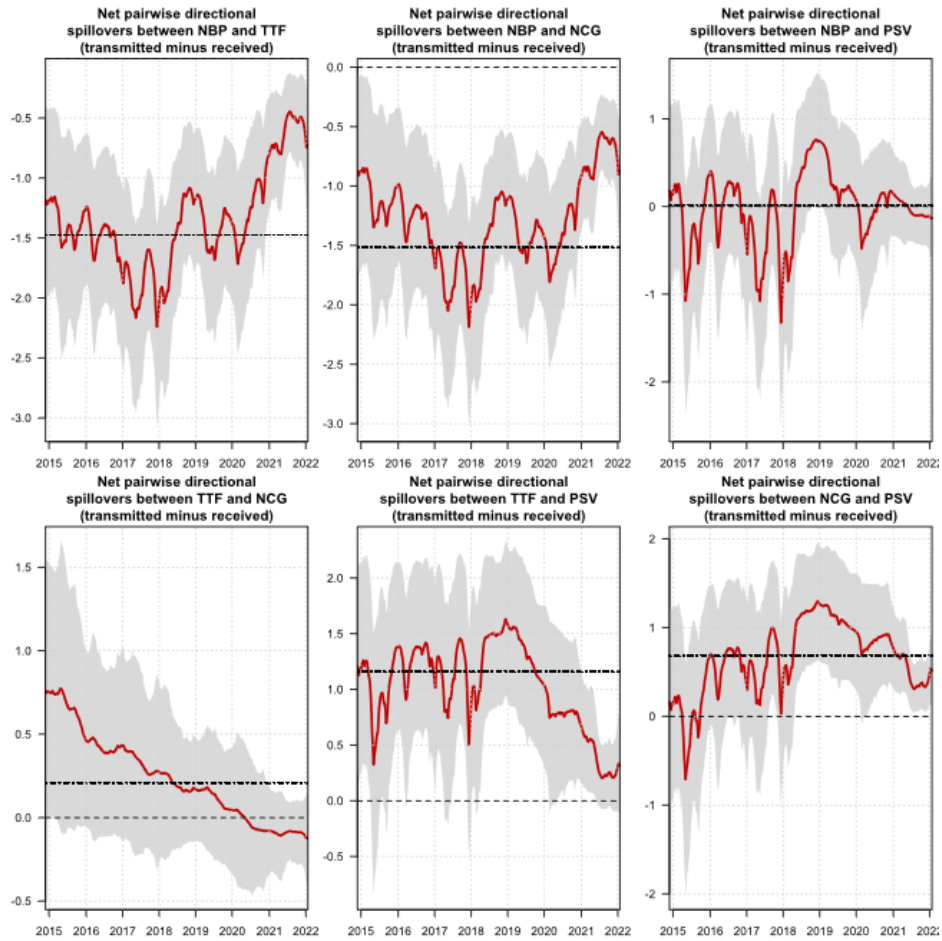
Figure 8. Net volatility spillovers for the volatility series.



The largest changes in this respect can be seen for the TTF (a decrease in the NSI from around 3% to below 1%) and for the PSV (an increase in the NSI from around -3% to -0.5%). Interestingly, a large jump in the NSI value for the NBP and PSV was observed in March 2018, i.e., when the 'Beast from the East' hit Europe, which illustrates how the price impulse at this period was sent from the north to the south of Europe through the volatility channel.

Next, Figure 9 outlines the net pairwise directional spillover for the volatility series. In the case of the NEW region hubs, the TTF dominates the other markets (NBP and NCG), whereas the NBP is a net receiver of volatility shocks. However, a very interesting result is that the dominance of the TTF over the NCG has been steadily eliminated over the investigated period. Regarding the PNSI between the Northern and Italian hubs, one can notice that the dominance of the TTF and the NCG over the PSV reached a peak in 2019 and has decreased steadily thereafter.

Figure 9. Pairwise net volatility spillover indices for the volatility series.



In general, the results obtained for volatility spillovers confirm and strengthen the results obtained for return spillovers. They clearly indicate that in recent years the gas market in Europe

has strengthened the level of integration and moved towards a state in which no single market strongly dominates other markets.

6. Conclusions

This paper has focused on the European natural gas market connectedness. We investigate four most liquid markets: three from the North-Western European region and one from the South European region. On the one hand, this selection allows us to conduct a direct comparison of our results with previous studies. On the other hand, it shows how the integration process between the North-Western region and the south of Europe progresses. To address the ongoing structural changes in the European gas market, we integrate the DY connectedness approach with the time-varying parameters VAR model with stochastic volatility. It allows us to quantify the dynamic connectedness between natural gas markets at each point in time with few restrictive assumptions.

Two results of our study seem particularly important. First, we have shown that the gas market in Europe becomes increasingly integrated. We observe a strong co-movement in prices across various markets. This indicates that although Russia remains the main gas supplier in Europe, it can no longer dictate prices to its customers. Secondly, we demonstrate that the two leading markets in Europe are the Dutch TTF and the German NCG. The former is distinguished by the largest and growing volume of trade, while the latter is the main channel for gas from Russia to the countries of North-Western Europe. Our results invalidate previous findings of Broadstock et al. (2020), which pointed to the leading role of the TTF and the NBP. However, in recent years, the observed dominance of the TTF and NCG has weakened, which can be partly attributed to the increase in the supply of the LNG and the launch of the pipeline from the Caspian Sea to Italy, via Southern Europe.

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